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# Developing a Risk Management System with an Optimistic Predictive Approach and Business Decision-Making

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**Abstract**

Risk Management is an important task that helps to monitor the business application to eliminate the political, financial, cultural, and social consequences. The organization's risk decision is affected by several characteristics, such as lack of accountability and risk decision-making. The difficulties are resolved by applying the Machine-Learning related Business Decision Making Approach (ML-BDMA). The created framework helps to reduce the difficulties in decision-making while managing the organization's risk. The Business Decision Making process works along with the Optimistic Predictive Techniques (OPT) that are used to identify the risk which leads to attaining the business objective. This process categorizes the risk according to the qualitative characteristics of business data. The system's effectiveness was evaluated using the experimental result in which the system ensures a 98.93% performance rate, 92.25% reliability rate, 93.47% authenticity rate, 91.11% risk management rate, and 97.77% development rate while making a business decision.

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**Keywords:** Risk management; Business Decision Making (BDM); Optimistic Predictive Technique (OPT); reliability rate and development rate.

## 1. Introduction

Risk management helps identify the risk and organizational planning measures taken to overcome the difficulties [1]. The risk assessment and priority are given to defining risks. Risk management is the method for choosing the best options or classifying the substitutes into a particular objective [2]. The greatest vision is to develop, safeguard, and improve shareholders' value by addressing difficulties that influence its objectives [3]. There are several potential causes and solutions to risk management problems, and many intrinsic elements are implemented for decision-making in the business platform [4].

Risk managers must always make high-level judgments depending on almost unrestricted data and restricted moments to evaluate and apply knowledge [5]. Unpredictability and business culture volatility often influence the effects of decision-making in managing risk [6]. The sector of finance is facing a similar circumstance [7].

Growing complexity with numerous contrasting aspects leads to numerous decision-making [8]. The financial crisis is one of the risk factors in business development; a correct decision-making strategy must be elaborated to overcome all the risk factors.

Decision-making is an important component of risk management [9]. The risk management team's capacity to make smart choices exists in risk management authority [10]. Risk assessment decision-making selects the finest options or positions the solutions to a particular risk management objective in business involvement [11]. Risk management problem-solving is the finest way to recognize risk in facilitating the business development framework. Risk is an important determinant of the risks to the business strategy. Risk management strategic planning lists serious risks according to requirements, including the risk exchangeable; the risk deeply impacts the company [12].

Risk modeling is one of the methodologies for evaluating risks [13]. The technology allows companies to identify key risks and advise on the appropriate measures for risk management [14]. Even then, decisions are focused instead on one component, which fundamentally affects the risks of corporate goals and core processes [15]. In practice, many considerations and decision-making options in risk management must be considered in business [16]. In advanced decision-making, scenario data is a key part of activities [17]. Real troubles nowadays include multiple data sources, some accurate and some unpredictable or contextual. Organized decision-making frequently occurs in the eyes of unpredictability as to the advantage or accident of a decision-maker.

Risk is the ability for a loss or unwanted result of a judgment. The new device assessment is more complex than the basic issue due to the cross-data risks and uncertainty of the price surroundings [18]. Almost every living choice carries certain risks, and certain judgments are considerably more dangerous. Risk and judgment are two interconnected strategic aspects relevant to various complexities. The starting point configuration greatly impacts risk management as a significant characteristic of comparison reliance [19]. In particular, decision-makers in conventional decision-making issues frequently consider the source statement. The adaptive judgment of decision-makers is sometimes unclear and irregular.

Consequently, the current system is often fixed as a starting point for the optimal solution, the principles of several other evaluated particles, and the predicted amount of all options. Vibrant duration marks of response are often used to resolve unclear and risk-taking issues in some incomplete data and complex environments. The academics often considered the feasibility of assessment with multiple visual references in a thorough study of inferential business statistics. In many risky decision-making issues, numerous data points are being used. The aspect of decision-making issues is measured by several frames of comparison under normal and abnormal conditions of business development. The main contribution of ML-BDMA is described below

- ✓ ML-BDMA is to develop a framework that ensures substantial risk management for business decision support.
- ✓ ML-BDMA is used to identify risks based on the goals of an organization and defines such risks qualitatively, utilizing them in business terms

The article is planned as follows: Section 2 deliberates contextual studies about Risk management for Business Decision-Making. Section 3 Explains the ML-BDMA that elaborates the risk making and supports business development. The effectiveness of the ML-BDMA-based risk management process is illustrated in section 4, and the conclusion is described in section 5.

## 2. Related Analysis of Risk Management for Business Decision-Making

DavideFioriti et al. [20] established an Economic multi-objective approach (EMOA). Depending on the outcomes of a new evaluation on a clear specific implementation, an EMOA framework is developed that optimizes the various economic measures together. A response analysis has been performed regarding electric power, load reduction price, and delivery policy. The findings indicate that a transitional specification of the EMOA approach representing a reasonable option among strategic criteria can fulfill the ecosystem's complicated designers.

Marijke De Couck et al. [21] introduced Decision-Making in Business Cases (DMBC). DMBC examines the impact of two inhaling trends on stress and decisions. Before and after the assignment, stress levels were automatically reported. Although the measures indicated increases in psychological stress, they did not. In the experimental class, respondents showed a considerable proportion of right answers compared to regulations. Such research shows that short vagal respiratory patterns increase heart rate and accurately enhance judgment.

Arafat SalihAydiner et al. [22] proposed Decision-making Performance (DMP). DMP corresponds to the existing data management research by examining interconnections among functionality and their impact on corporate productivity. A set of assumptions that consider the decision and business productivity as mediator factors are developed to explore these relationships from a resource-based perspective. The results were gathered to conclude the implemented sequential framework by which decision-making and business process efficiency play an important part in global resources and organizational functionality.

EdmundasKazimierasZavadskas et al [23] introduced Multiple-Criteria Decision-Making (MCDM). MCDM is focused primarily on three regions: description of providers and distribution of rational orders, assessment of and selection of products or amenities, and choice of personnel/partner. Many new methods that should appeal to the scientific community are suggested. The advanced decision management process is a popular framework. MCDM has developed a variety of decision-making methods to model complicated business requirements.

Wen Song et al. [24] discussed A multistage risk decision-making method (MRDMM). The standard cloud framework assessing the conduct qualities by MRDMM and the risk-making multistage issue is analyzed. First, the relatively entropic and altered comparative evaporation is described as location measurements for the standard public cloud from the standpoint of full use of data. Furthermore, behavioral economics extends to a standard set of cloud models. The alternative options are ranked according to the final scoring norms.

KangningZheng et al. [25] introduced risk decision-making (RDM). In decentralized, partly centralized, and fully centralized decision-making, RDM uses a three-level orbit manufacturing process consisting of a space station manufacturer, provider, and transportation provider technologist. The spacecraft developer's optimum inventory levels and the provider's blockchain implementation level are shown with the spacecraft fabricator transition's risk correlation for each situation. In three decision situations, developers often evaluate the increased income of the production process [26, 27].

Based on the survey, ML-BDMA is developed for managing the risk for business decision-making. ML-BDMA identifies risks based on an organization's goals and qualitatively evaluates the standard risk classification in business terms.

## 3. Proposed machine learning-based Business Decision-Making Approach (ML-BDMA)

This paper discussed Machine learning-based business decision-making to improve business performance. The trading volume and asset price of a financial product or instrument in a network environment are affected by various complicated variables. Machine learning and risk analytics offer important tools for gathering a large amount of information from our website and gathering practical information to predict related entities' financial risks accurately. This article analyses the extent of the risk of exchange and the price of assets. Business analyses can access business data via Support Vector Machine (SVM) and Artificial Neural Network (ANN). The integration of the risk management method develops nonlinear RMS-based mining modeling. In addition, online knowledge has been transformed into financial principles, a major input for machine learning models. Empirical studies show a strong association between asset price volatility and the well-captured and processed SVM sense of information. The aggregated statistics show that the RMS-based SVM system is available under sliding time windows to achieve reasonable projected efficiency. Firstly, the dataset used to produce better results should be expanded. The second important approach to evaluating posts' emotional polarity is to create a more efficient sentiment calculator algorithm.


Figure 1: Basic Diagram of Risk Management

Figure 1 shows the Basic Diagram of Risk Management. Any company has to implement a risk assessment process. Organizations or insurance agencies' provision of their clients should not be resource-intensive or costly to good risk management. A little formalization, structure, and strong organizational experience will fulfill the risk management process. Risk management demands such commitments in time and money to be substantial to succeed. It would be more likely to be employed and sustained when introduced progressively over time.

The four main types of hazards include hazard problems such as collisions. Financial threats, like attrition and supplier failure; Operational risks, including global recession; competitive risks; and the market reputation of emerging rivals. In the financial risk, the business may lose money, creating difficulties in terms of liquidity, credit, and operational risk. The directors' major decisions on the goals of an organization come from strategic risks. To calculate their risks, many companies use a heat map. A risk map is a graphic guide that provides descriptions of which threats are common and severe (and thus require the most resources). Risk management decision-making can recognize very unlikely or low-impact, high-trusting, and important impacts.

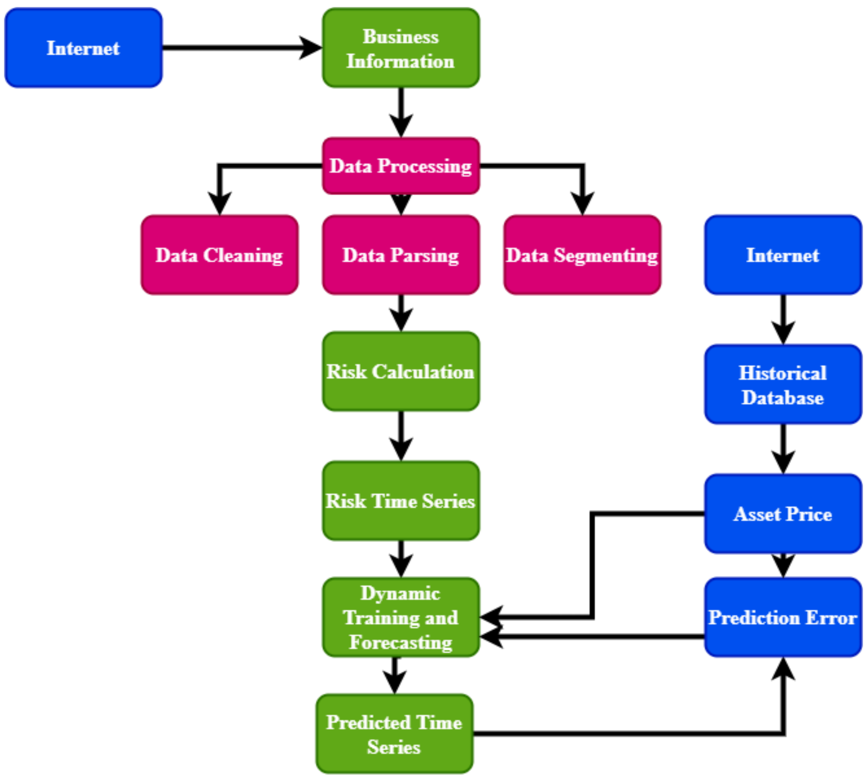


Figure 2: The proposed ML-BDMA

Figure 2 illustrates the proposed ML-BDMA. It may be inaccurate to reflect the amount of financial information and compromise the prediction's effectiveness. The deficit by examining its contents to fully assess the effect of the online information on financial time series; The online common sense knowledge foundation unfolding interconceptual relationships and inter-attribute linkages between concepts, as defined in English lexicons, are used to discuss risk measurement for all news pieces by keywords. Any news item is broken down and changed into a keyword array in the same series as in the market, each with a separate danger, depending on the net term. A combination of both feelings of the keywords will make the final decision for the entire business. The Risk Time Series is achieved and fed as one of the exogenous inputs into the machine learning system, particularly SVM. Through assigning feelings to a listed firm as part of the vector function, a quantitative examination of the nonlinear association between news feelings online and financial volatility. Data cleaning is how wrong, corrupt, wrongly formatted, duplicated, or missing data is fixed or deleted within a dataset.

There are many possibilities for data to be duplicated or wrongly labeled by merging many data sources. Data parsing is a mechanism by which one data string is translated to another data form. An analyst takes the HTML mentioned above and transforms it into a descriptive, easy-to-read, understandable data format. A division or subset of the activities of a company, especially in large companies. To be regarded as a data unit, a business division has to generate direct sales for the organization. Each Section's expenditures and earnings are paid internally and known as a data segment. Financial risk management practices fast economic valuation within a company using financial instruments to handle risk: credit risk, inflation risk, business risk, market risk, liquidity risk, exchange risk, legal risk, business risk, and reputational risk. Risk management is the practice of the firm's financial risk management. Financial projections are the method for measuring or projecting a company's potential performance. The most popular form of the financial forecast is a revenue report. All three financial statements are forecast in a comprehensive financial model. Risk assessment in the financial sector involves identifying, analyzing, and embracing or mitigating investment decision-making volatility. Volatility is mathematical proof of how big the values of a commodity fluctuate around its average price. Volatility measurements are made in several ways, including beta coefficients, price models of options, and normal return variations. Stock volatility means a dramatic decline or rise in the valuation of a given stock for a given period. The price of a commodity exchanged, and its volatility has a relationship.

One of the most significant and, at the same time, realistic objectives is the prediction of uncertainty for all those that assign risk and participate in capital markets. The volatility of asset returns indicates the extent to which returns fluctuate. Acceptance of the risk means that certain risks are unavoidable in conducting business, and the benefits of an activity outweigh the risks. Risk transfer means that another company is liable for any bad results, as in an organization. Establish a systematic procedure that objectively and systematically implements its solution and supports workers at every phase. The organization's risk management process is increasingly formalized, and a risk culture has developed. The decision to make more informed decisions is based on a full overview of its business climate and create a better over the long term.

Volatility means the standard deviation or volatility of the value change in the financial instrument for a given duration. The risk management method (RMS) is commonly used to model financial time series, which show time-varied volatility clusters. The proposed creation of an RMS in this Section by including financial details in the normal framework.

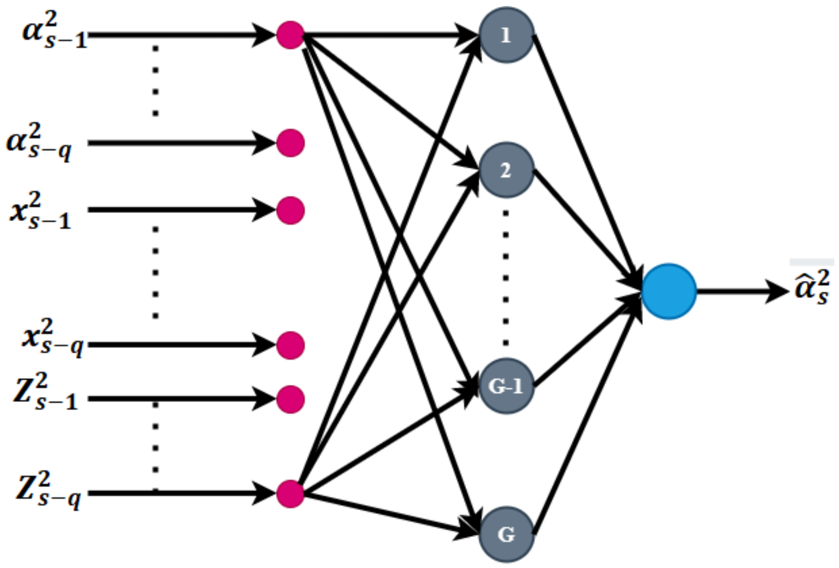


Figure 3: Basic Diagram of machine learning-based business Information Classification

Figure 3 depicts the basic diagram of machine learning-based business information classification. Machine learning is the central strategy to bridge the volume of knowledge and the time series for trading volumes. Testing learning models based on training samples from current data sets may provide new predictions. The proposed proposal The ANN RMS-based feed is the neural network for a 3-component feed, in which$\alpha_s^2$represents the uncertainty forecast on day $s$, $x_s^2$ indicates the regular rate of square trade change and $Z_s^2$represents the daily amount of financial data squared. The elements $x_s^2$to $Z_{s-q}^2$are the autoregressive portion of the model, while the elements $x_{s-1}^2$to $Z_{s-q}^2$are the moving average component. The input vector size is the $Q+P+r$the hidden layer contains $G$ units, and the output vector size is 1.

The volatility is calculated in the daily volatility model Section by a daily volatility model.

$$X_s = \varepsilon_s + \mu_s \quad (1)$$

Figure 3 depicts the basic diagram of machine learning-based business Information Classification. As shown in equation (1), a Modified nonlinear RMS has been determined. $X_s$is a daily return, $\varepsilon_s$ represents the deterministic mean return,$\mu_s$ denotes the shock, residual, accuracy error, and innovation. In equation (2) information set is evaluated by:

$$(\varepsilon_s|\varphi_{s-1})\sim M(0,\alpha_k^2)$$

$$\alpha_k^2 = \sigma_0 + \sum_{j=1}^{q} \sigma_j\, \alpha_{s-j}^2 + \sum_{i=1}^{p} \gamma_j\, \mu_{s-j}^2, (\sigma_0 > 0, \sigma_j, \gamma_j \geq 0) \quad (2)$$

As found in equation (2), the information set by time has been calculated.$\varphi_{s-1}$represents the information set varying through by time $s$, $\alpha_k^2$ is a time variance parameter. N is an innovation. Our solution is to replace either the trading volume or the advantage price with the regular change in a daily changing rate$X_s$ and $\sigma_0$ is a residual function. $j$is a response function.

The RMS showed that $\mu_s$ depends on certain exogenous inputs that influence the instability of the finances. The RMS relies on the information set at time $s$ as its dependent distribution. Parameter $\gamma_j$equation(2) explains the immediate response of stock return to new market developments, mostly by financial news. Given these variables, it is justifiable to identify the number of financial details for a variety of $\mu_s$ in equation (3):

$$\mu_s = x_s - \delta$$

$$\mu_s = E_s(Z_s, \mu_s') = h_s(Z_s) + \theta_s \mu_s' \quad (3)$$

As inferred in equation (3), financial information varying with time has been computed. Where $\delta$ is steady and is the amount of online financial information $Z_s$ on day $s$. $E_s$is expressed as the accuracy of error, $h_s$ is financial volatility. A modified RMS can, therefore, be expressed as (4):

$$X_s = \varepsilon_s + \mu_s$$

$$(\varepsilon_s|\varphi_{s-1}) \sim M(0, \alpha_k^2)$$

$$\alpha_k^2 = \sigma_0 + \sum_{j=1}^{q} \sigma_j\, Y_{s-j}\left(\alpha_{s-j}^2\right) + \sum_{i=1}^{p} \gamma_j\, \varphi_{s-j}\left(x_{s-j}^2\right) + \sum_{l=1}^{p} \beta_l\, \theta_{s-l}(z_{s-l}^2) \quad (4)$$

As calculated in equation (4), Modified RMS has been determined. When the three-time delays reflect the three unknown functions $q, p, R$, and $Y_{s-j}$,$\varphi_{s-j}$,$\theta_{s-l}$denotes the nonlinear relationships are undetermined.

Let $u_s$ indicate its trading volume for a certain market or index on day $s$, the regular rate change $X_s$ for trading volume in equation (5):

$$X_s = ln\frac{u_s}{u_s - 1} \quad (5)$$

As deliberated in equation (5), daily return rate change has been evaluated. If $C$ is defined as the calculation window duration, the volatility of $\ddot{\alpha}_s^2$ can be achieved by measuring the $X_s$variance within the $(s - C + 1)$and the timing of day in equation (6):

$$\alpha_s^2 = \frac{\sum_{j=0}^{C=1}\left(X_{s-j} - \overline{X_s}\right)^2}{C-1}$$

$$\overline{X_s} = \frac{\sum_{j=0}^{C=1} x_{s-j}}{C} \quad (6)$$

The volatility of time variance $\alpha_s^2$ and $\overline{X_s}$ refers to daily return variance has been determined in equation (6), $\alpha$ expresses the time variance coefficient, $X_{s-j}$ denotes the daily return varying by time $s$ with a response. Such regular volatility is determined based on a certain slipping longitude volatility window. Each day's change reflects the exchange value from the previous few days to the present.

The time window-dependent models for volatility are discussed in this Section. The decision-maker can obtain a better picture of the movement of volatility from a time window model in a macroscopic way and is particularly useful for mineral associations of knowledge decision and volatility

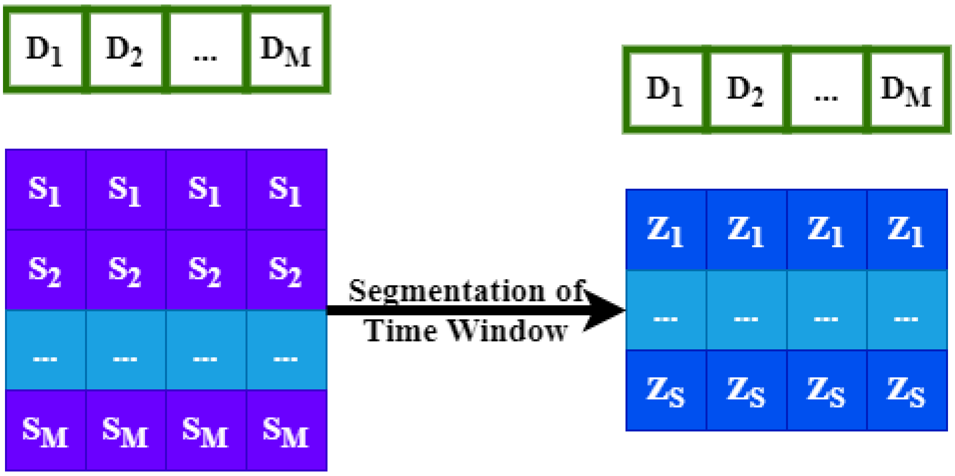


Figure 4: Time window of segmentation.

Figure 4: demonstrates the Time window of segmentation. This approach begins with a phase of time segmentation. Suppose there is no trading action on financial exchanges over weekends. In that case, $S$, a one-week time window, is used for breaking down the entire period into several different timescales, each for one week, as seen in Figure 4. $M$is the average number of operating days for all businesses, and $S$ represents the total time windows. Assume that the window length is $K$ and get$M = S * K$. Due to the varying range of trade dates that different listed firms have, date unification is a necessary measure that is visualized.

Figure 5, where the $N$ cumulative number of business days for any of the firms mentioned in the list is $M_i(i = 1,2, \ldots N)$reflecting a pre-set period for the number of businesses. The process of separation and unification is extended to the quotes of all the companies listed.

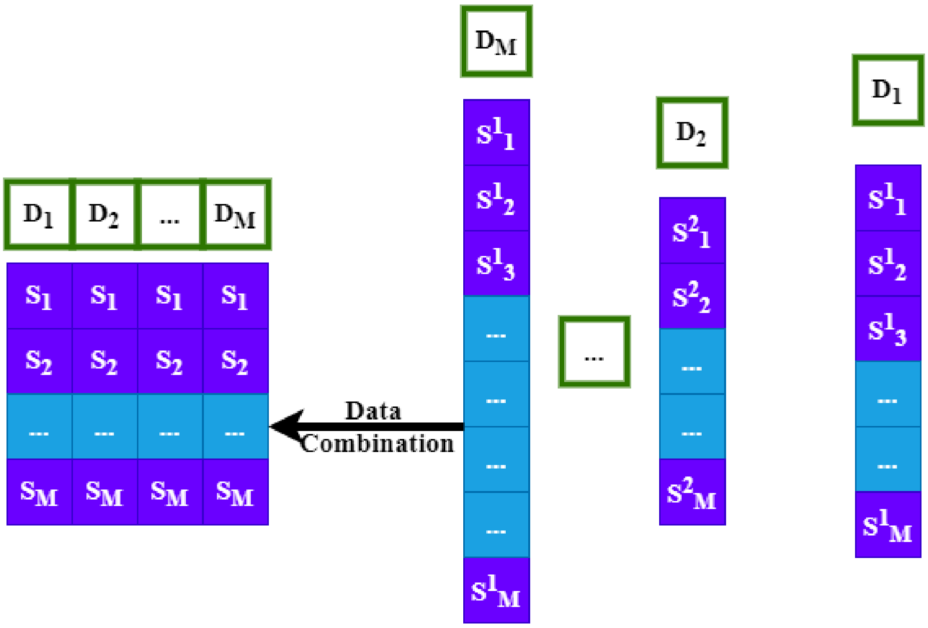


Figure 5: Representation of the Data Combination Window

Let $Z_j$ mark the window of time. The closing price and amount of dealing are denominated $q_s$ and $U_s$ for the day on which the trade is held under $Z_j$. This window has $K$ days, and the starting day is referred to as $S_j$. The volatility of the asset prices can be described in this window in equation (7):

$$\alpha_j^{q^2} = \frac{\sum_{s=S_j}^{S_j+K-1}\left(x_s^q - \overline{x_s^q}\right)^2}{K-1} \quad (7)$$

As described in equation (7), the asset prices' volatility with the window has been described. If $X_s^q$ is the shifting asset market trend on day $s$, $K$ is the time window period in equation (8):

$$\overline{X_s^q} = \frac{\sum_{S=S_j}^{S_j+K-1} X_s^q}{K} \tag{8}$$

The above equation has formulated the asset market trend (8). Similar formulas may be applied to the rate of trade applied in equation (9):

$$\alpha_j^{u^2} = \frac{\sum_{S=S_j}^{S_j+K-1} (X_s^u - \overline{X_s^u})^2}{K-1} \tag{9}$$

The trade rate has been obtained in equation (9). As the volatility of the trade volume rate in $Z_j$ equation (10):

$$\overline{X_j^u} = \frac{\sum_{S=S_j}^{S_j+K-1} X_s^u}{K} \tag{10}$$

The trade volume rate volatility has been found in equation (10). The phenomenon of the SVM optimization problem can be formulated as follows in equation (11):

$$\frac{1}{2} Z^S Z + D \sum_{j=1}^{N} \delta_j \tag{11}$$

As described in equation (11), an optimization problem has been discussed. Where $j = 1,2, \dots N, \delta_j \geq 0$ is the assignment cost margin of error. The $X_j$ classification of the $j$and$\delta(Y_j)$ lines transforms space $Q^N$is observed in equation (12):

$$X_j[Z^S \delta(Y_j) + a] \geq 1 - \delta_j \tag{12}$$

As deliberated in equation (12), observation classification has been performed. The main benefit of this is that $\delta(Y_j)$ is not considered for its practice kernel feature for evaluated $L(y) = L(Y_j, Y_i)$In operation. is used, which allows for vectorized implementation$L(y) = \delta(Y_j)^S \delta(Y_i)$.The kernel function is an SVM entry and a solution for the optimization target. Different types of kernel functions, including linear, Gaussian, or polynomial functions, vary in their mathematical formulation and ability to make accurate forecasts in integration, training in equation (13):

$$L(Y_j, Y_i) = e^{(-\omega Y_j - Y_i^2)} \tag{13}$$

Equation (13) is referred to as a 'radio-based function' (RBF), $\omega$ is positive. In terms of nonlinear classification tasks or non-separable datasets, the RBFs are the most used kernel functions since they are strongly predictable. Since the paper addresses non-separable business data, RBFs can provide new insights into CE implementation. The proposed ML-BDMA has improved business performance and enhanced decision-making to achieve the performance rate, reliability rate, risk management rate, authenticity rate, and development rate.

## 4. Result and discussion

ML-BDMA has been evaluated based on performance and reliability. Trustworthiness is a critical element in almost every business decision-making. The system likely performs its necessary task for a given period under some circumstances. A secure and prolonged system can be operated to reduce risk management. The proposed ML-BDMA covers several reliability aspects, including information reliability and efficient risk management. ML-BDMA includes a scheme for managing an enormous number of product data sources, including integrated business and a production mechanism for reducing risk management. The performance rate of ML-BDMA is shown in Figure 6.

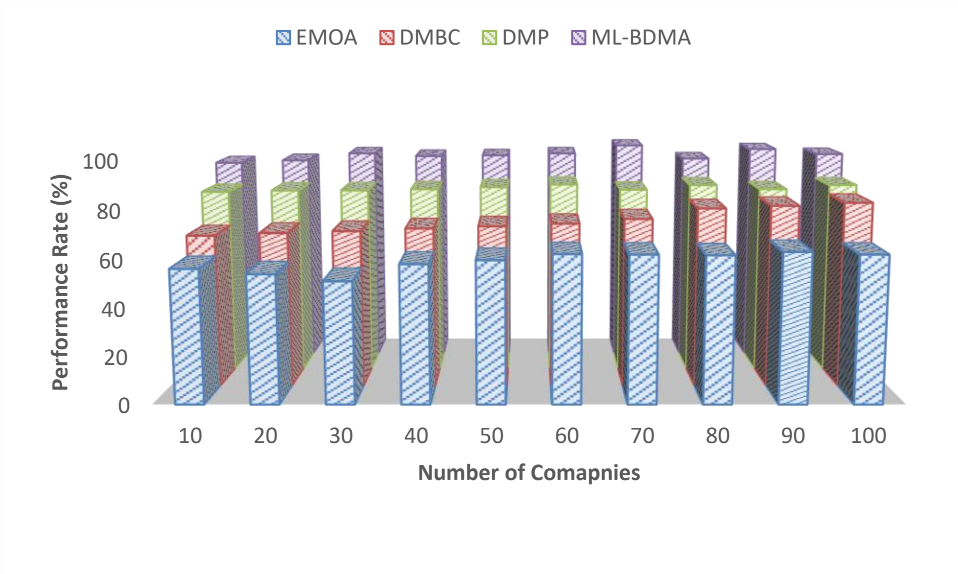


Figure 6: The performance rate of ML-BDMA

In general, production handling in businesses is strongly equipped to supply data for predictive maintenance and checks with several devices to ensure system reliability and economic stability ML-BDMA is used to diagnose sharpening defects in business production. ML-BDMA discrete prolonged functionality and then summarises the information via risk management. The discrepancy amount can be obtained accurately from the frequency distribution for different spatial subgroups. The reliability rate of ML-BDMA is shown in Figure 7.

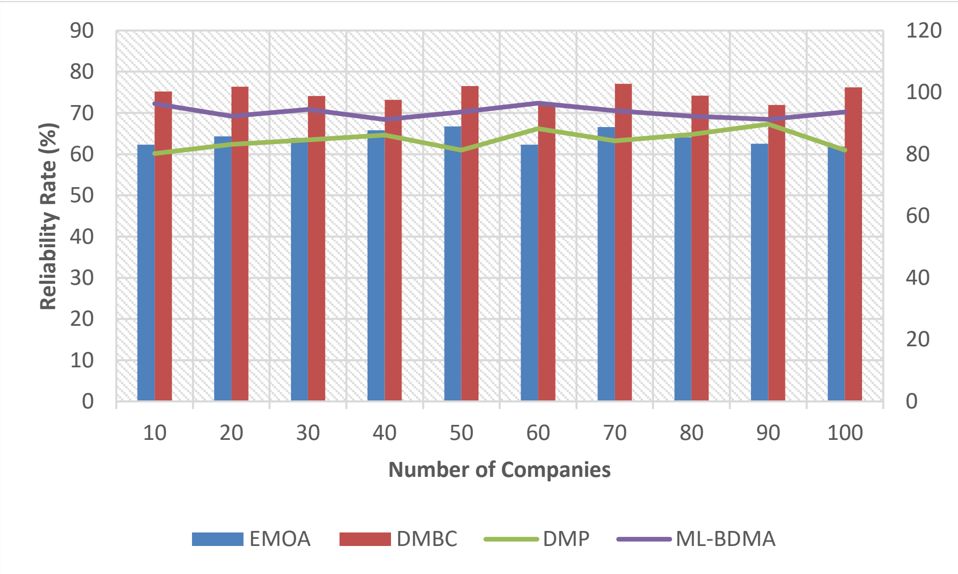


Figure 7: The Reliability rate of ML-BDMA

There are various systems and activities in the business sector, independent of their particular evolution. In business decision-making, all sorts of risk management are predicted because of all risk and unpredictability in the actual world. Risk management is an unintended occurrence detection for evaluating its effects and a judgment to alter the scope documents' trajectory. Under business decision-making description and idea, a framework and logic method for the optimized feature is achieved to achieve an efficient and supportable risk management rate. The risk management rate of ML-BDMA is shown in Figure 8.

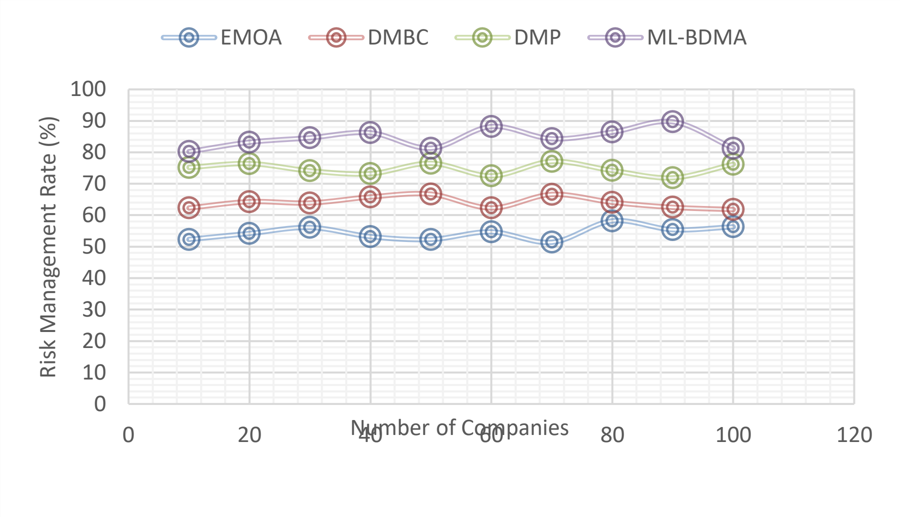


**Figure 8: The risk management rate of ML-BDMA**

The popular methods for economic risk reduction are purchasing and selling financial products in the business. An investment in the forward agreement includes the retailer of the agreement, at a certain corrected point in time, to produce a pre-specified amount of products or property in business development. In contracts, the capacity to throw in adjusted pricing is the main risk-reduction component for producers and consumers. International corporations are commonly used for managing abroad transaction risk in economic valuation adjustments. The financial risk management rate of ML-BDMA is shown in Figure 9.

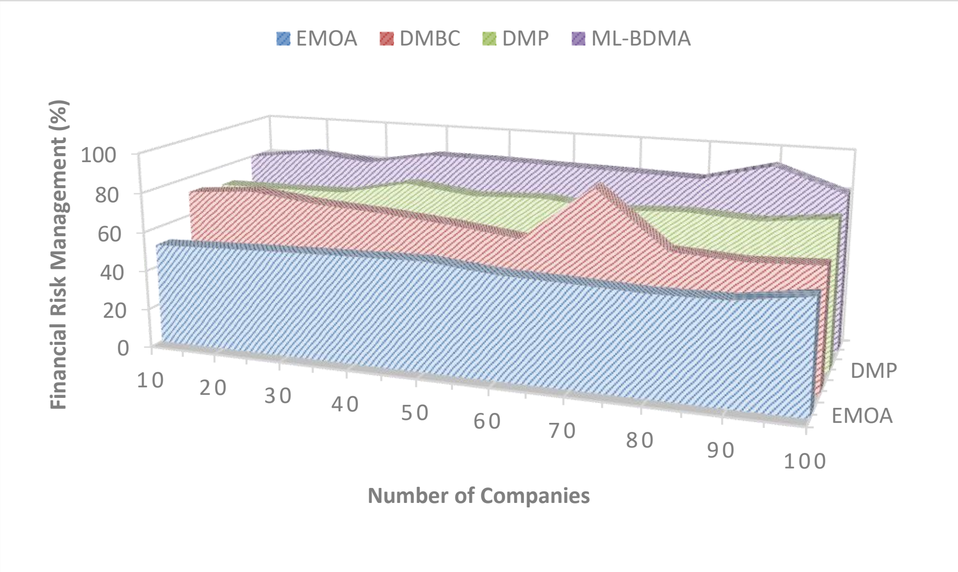


Figure 9: The financial risk management rate of ML-BDMA

The measuring model considers the connection between the structures and their objects to test the business decision-making authenticity. The interconnected risk management structure established here has consequences for managers' corporate finance and economic management studies. Discrepancies and finite-risk management solutions provide the core for business and theoretical implementation models that relate numerous ambiguities to business development companies and established firms. The description of motivational techniques to insecurities shows a wide range of business activities, most of which were not considered risk management schemes. The authenticity rate of ML-BDMA is shown in Figure 10.

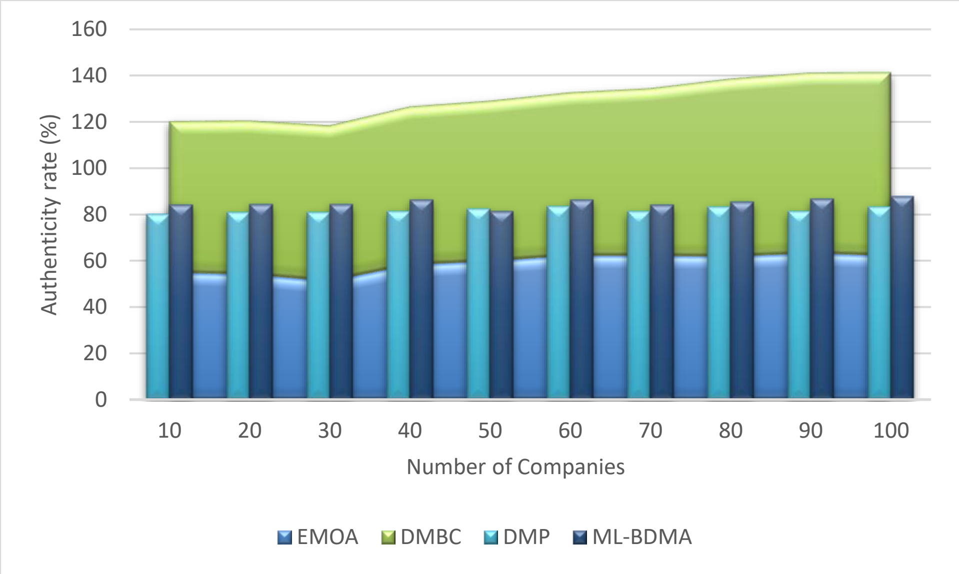


Figure 10: The authenticity rate of ML-BDMA

The development of business risk management actions is not confined to evaluating loss exposures and applying relevant economic risk management practices such as protection and profits. Risk management leads to financial and operational reactions that are rather interconnected, and decision-making in both fields would have been inadequate to isolate the other. Businesses can grow their range of alternative actions by evaluating their economic and operational reactions to formulate risk management answers before facing uncertainty risks. The development rate of the business is shown in Table 1.

Table 1: The development rate of business

| Number of Companies | EMOA | DMBC | ML-BDMA |
|---|---|---|---|
| 20 | 78.90 | 88.90 | 95.33 |
| 40 | 75.66 | 85.67 | 94.22 |
| 60 | 74.32 | 83.22 | 96.23 |
| 80 | 77.46 | 89.67 | 93.67 |
| 100 | 72.10 | 87.44 | 97.77 |

The effective risk management viewpoint often strengthens the fact that it encourages understanding trade-offs among different uncertainties exposed. Reducing ambiguity in one aspect could lead to greater exposure to another. For instance, a business with exchange rate claims may desire to safeguard its international commodity exposure. The foreign exchange for the domestic currency is sold forward to reduce the business model's risk. The efficiency of the ML-BDMA is shown in Table 2.

Table 2: The development rate of business

| Number of Companies | EMOA | DMBC | ML-BDMA |
|---|---|---|---|
| 20 | 62.45 | 68.90 | 93.33 |
| 40 | 71.22 | 74.56 | 90.11 |
| 60 | 66.78 | 78.90 | 96.44 |
| 80 | 78.90 | 67.33 | 98.56 |
| 100 | 75.33 | 69.23 | 97.11 |

The proposed method achieves the highest performance and efficiency when compared to other existing Economic multi-objective approaches (EMOA), Decision-Making in Business Cases (DMBC), and Decision-Making Performance (DMP).

## 5. Conclusion

This paper presents (ML-BDMA for machine learning that provides the right support for risk management in creating a framework that guarantees significant risk decision-making. Optimistic predictive technology is used to identify risks based on an organization's objectives. ML-BDMA qualitatively defines such risk as a company by a standard risk categorization. Risk management is essential since it helps companies monitor and sometimes prevent financial, economic, political, and cultural risks. Inadequate risk management, the strategic structure, and a lack of responsibility for a company's risk decisions provide challenging risk decision-making qualities. The experimental results achieved the highest performance rate (98.93%)and reliability rate (92.25%), risk management rate (91.11%), authenticity rate (93.47%), and development rate (97.77%) efficiency based on business decision-making.

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